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Drivers of the Resource Adequacy Contribution of Solar and Storage for Florida Municipal Utilities

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Abstract

Solar's variable generation limits its contribution to reliably meeting peak demand, or its resource adequacy contribution. Energy storage is a leading option to increase solar's resource adequacy contribution, yet the contribution from different configurations of solar and storage is not widely understood. We develop methods for exploring the primary drivers of an estimate of the resource adequacy contribution of solar and storage, and we apply the methods to a case study in Florida, where demand peaks in winter and summer. We find that the portion of solar nameplate capacity that contributes to resource adequacy—its capacity credit—is less than 50% and that it declines with increasing solar penetration. The capacity credit of storage, even though it is fully controllable by the system operator, strongly depends on the duration of storage. The capacity credit of 1 hour of storage can be less than the capacity credit of solar. Achieving a 90% capacity credit requires at least 4–5 hours of storage when storage capacity is small relative to the system peak. As storage deployment increases to 20% of the peak demand, 9 hours—and sometimes more than 10 hours—of storage are needed to achieve a 90% capacity credit. Increased solar deployment at the system level can increase storage's capacity credit. Directly pairing solar and storage can also impact the capacity credit. Storage with a power rating similar to the solar inverter rating loses capacity credit when coupled with solar if its duration is more than 1–2 hours, because storage competes with solar for use of the inverter. On the other hand, there is no reduction in capacity credit when the storage is small relative to the solar inverter. The approach and tools developed here for exploratory analysis can be useful for many other utilities and regions grappling with similar preliminary questions, prior to evaluation of specific cases using more detailed and resource-intensive modeling.

Key words: capacity credit; resource adequacy; solar; energy storage; pv; utility planning

Table of Contents

List of Figures

List of Tables

1. Introduction

The contribution of solar photovoltaics (PV) to reliably meeting an electric power system's peak demand—solar's **resource adequacy contribution**—is limited owing to the inherent variability in generation from the changing position of the sun along with passing clouds. Increasingly, energy storage has been considered a leading option to improve solar's resource adequacy contribution, yet the contribution for different configurations of solar and storage is not widely understood. Further, the overall capital cost of storage increases with longer durations [1], driving systems to be designed with durations only long enough necessary for a particular application. We develop methods for exploring the primary drivers of an estimate of the resource adequacy contribution of solar and storage, and we apply the methods to a case study in Florida, where demand peaks in the winter and summer.

The contribution of different technologies to resource adequacy is important for two primary reasons: (1) ensuring that a power system is reliable requires that sufficient resources are available to meet demand, even with generation outages and variability in generation; and (2) if a technology contributes to resource adequacy, then it can displace or defer the need to build other resources that would otherwise be needed, leading to economic value. We refer to this economic value as the **capacity value** (in monetary terms), whereas we refer to the percentage of a generating technology's nameplate capacity that can be counted toward meeting resource adequacy requirements as the **capacity credit (CC)**.

The CC of energy resources is particularly important in long-term utility planning. It can be one of the key assumptions affecting resource selection in the capacity-expansion models frequently used in integrated resource planning [2]–[5]. The National Renewable Energy Laboratory's (NREL's) Resource Planning Model (RPM), for example, develops a CC estimate for different resources to find least-cost portfolios of resources that meet projected grid needs [4][1]. This model is currently used to quantitatively evaluate various scenarios associated with accelerating the deployment of solar and storage in Florida through a partnership with several municipal utilities, the Florida Office of Energy, and other key stakeholders [7].

The limitations on solar's CC—due to variable cloud cover and the timing of sunlight versus the timing of peak power-system demand—are well understood [2], [8]–[14]. Probabilistic methods are widely accepted as an accurate way to calculate the CC of solar (and wind), with several approximation methods developed to reduce the large data and computational needs [15]–[17]. Also understood is the decline in solar's CC with increasing solar penetration on the grid, as the net peak (system demand minus generation supplied by variable resources such as solar) shifts into

[1] In RPM, conventional resources are assumed to contribute their full nameplate capacity toward meeting planning reserve margins [6].

hours without strong sunlight [2], [18]. Many detailed evaluations of solar's CC focus on regions that have their highest peaks on summer afternoons (e.g., much of the western United States), but solar's CC is smaller in regions with winter night peaks. Relatively few studies focus on regions with a dual-peaking pattern, where summer cooling loads are nearly equivalent to winter heating loads.

Understanding is much more limited with regard to the factors affecting the reliability contribution of energy storage, and estimates of storage's CC are sparse in the literature. Sioshansi et al. [19] use probabilistic methods to quantify the CC of different storage durations for various U.S. utilities. They show that the CC of long-duration storage (8–10 hours) approaches 100%, while short-duration storage (1–2 hours) achieves only about half that value. They highlight the importance of accounting for the probability of subsequent outages, through dynamic programming techniques, when estimating the CC. They demonstrate that previous estimates of storage's CC with probabilistic techniques from Tuohy et al. [20] do not account for subsequent outages and therefore represent maximum estimates. These studies assume storage is dispatched to maximize its arbitrage value, and then they evaluate the CC associated with that dispatch. They do not indicate the degree to which the CC could be increased if storage's dispatch were optimized to maximize CC. Zhou et al. [21] develop a more general framework for evaluating the CC of storage and demand-side resources, noting the interplay between energy capacity and power capacity in determining the CC. Nolan et al. [22] similarly focus on demand-side resources and highlight the dependence of the CC on the characteristics of customer loads and timing of system-wide peaks.

Solar and storage can also interact to affect the CC of both technologies, though these interactions have only been studied in a limited number of regions. Denholm et al. [23] identify a declining CC of storage with increasing storage deployment, because the remaining load peaks become wider as storage clips off more peaks. However, they show that high solar penetrations in California can narrow net load peaks and delay the decline in storage's CC. Interactions between solar and storage using probabilistic reliability techniques have also been investigated in Singapore [24] and Ontario, Canada [25]. Aside from peak impacts, solar and storage also impact net load ramps [26]. Recent studies demonstrate the economic value associated with flexible solar plant operation and the tradeoffs relative to storage [27], though we limit our focus to the CC and do not investigate the implications of these operational issues.

We expand on this previous literature in four ways. First, we focus on a state in the Southeast, a region with a growing share of U.S. solar deployment where dual-peaking loads are common. Second, we develop a method for finding the storage dispatch that maximizes the CC as defined in NREL's RPM. Third, we evaluate the impact of different solar + storage configurations on CC, particularly with respect to coupled storage and PV. Finally, we validate the method for approximating the CC of resources with a detailed probabilistic method.

The approximation method used here is convenient for easily and transparently evaluating the CC of solar and storage under many different possible weather years, combinations of hypothetical sites and utilities, and system configurations. This approach, which is validated against more detailed methods, can be useful highlighting general directional relationships and identifying where more detailed analysis is warranted. In the next section, we describe the approximation method used within RPM to estimate CC as well as our method for finding a storage dispatch that maximizes storage's CC. Section 3 describes the data for our Florida case study. Section 4 presents our results, including the drivers of solar's and storage's CCs individually as well as the impacts of combining solar and storage. We also validate our approximation method relative to detailed probabilistic methods and evaluate the importance of forecast accuracy. We find that the approximation method provides similar, though somewhat higher, estimates of the CC for the large utilities but, as explained further in Section 4, overstates the CC of storage for a small utility with relatively large generators. We conclude in Section 5 with recommendations for future research.

2. Methods

Our approach enables broad exploration of the many factors that affect solar and storage CCs, rather than detailed quantification under specific configurations or circumstances. We approximate CCs using the load duration curve (LDC) method employed in NREL's RPM [4]. We then validate this approach by comparing the LDC approximation with CC calculations from the probabilistic effective load carrying capability (ELCC) method.

2.1 Load Duration Curve Method

The LDC method approximates the CC of a variable energy or energy-limited resource, such as storage, based on the reduction in the average highest **peak net load** hours relative to the average highest **peak load** hours. The calculation method can be visualized as the difference between an LDC, which sorts the load from the highest to the lowest over a specified period such as a year, and a net LDC during the peak hours (Figure 1). The net LDC is created by first reducing the hourly load by the corresponding generation from the resource in the same hour and then sorting the resulting net load from highest to lowest. Because the load and net load duration curves are sorted independently, the gap between the load and net load duration curves represents the decrease in the highest net load hours, irrespective of when they occur. This method can therefore capture any effects where deployment of a resource leads to a shift in the time of day that the net load peak hours occur. In the case of storage, the net LDC is created by both reducing the load by the energy generation from discharging storage and increasing the load by the energy required for charging storage.

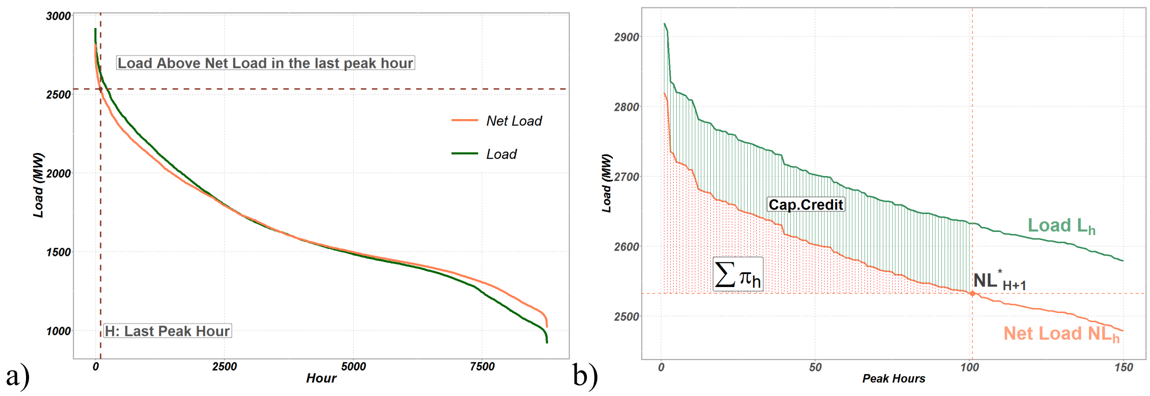

Figure **1**. Illustration of load and net load duration curves with storage for all hours of a year (a) and focusing on just the peak hours of a year (b).

Because of the influence of weather on CC, we calculate the CC over two timeframes. For the majority of the results we use 11 different historical years and calculate the CC separately for each year. This way we are able to see how sensitive the results are to the choice of one particular year. In each of these cases, we use the top 100 hours of the year (the top 1.1% of hours) as peak hours. We also, however, calculate the CC using all hourly data across 11 years at once. The CC using all hourly data across 11 years at once is arguably the most accurate way to estimate the overall contribution of a resource toward reliability. Long multi-year datasets are not always available, however, leading to individual years often being used in practice. This 11-year CC uses the top 1,100 hours (also the top 1.1% of hours) as peak hours.

2.2 Storage Dispatch Model

Though the LDC method can approximate the CC of storage, it does not directly specify the dispatch schedule for storage. To estimate an upper bound to the CC, we develop a linear model whose solution maximizes the CC of storage, where the CC is defined based on the LDC method. The approach leverages insights from the literature on optimizing the conditional value at risk (CVaR) [28], [29] and the fact that maximizing the CC of a resource, based on the LDC method, is equivalent to minimizing the area under the net LDC in the peak net load hours. Because the resulting optimization model is linear, it can be solved extremely quickly, even when considering 11 years of hourly data. Additional details explaining the analogy between the CVaR literature and the model for maximizing the CC of a resource are provided in the Appendix.

An energy storage system is characterized by its nameplate capacity (MW), its energy capacity (MWh), and its roundtrip efficiency. We assume the storage system charges and discharges at rates up to its nameplate capacity. The storage duration (in hours) is therefore the ratio of the energy capacity to the nameplate capacity. The analysis uses hourly time steps—no shorter time constraints or ramping limits have been considered. The model also assumes perfect foresight over the whole analysis period.

Because the model searches for an optimal storage dispatch profile, the hourly system load net of storage generation (the net load) is also a decision variable obtained from the model. The level of the net load just outside of the peak net load hours, NL^*_{H+1}, is especially significant, as it defines the area of the net LDC that when minimized leads to the storage dispatch with the maximum CC. More details about the NL^*_{H+1} variable can be found in the Appendix.

The calculation details are as follows:

1. Indexes and Parameters

h	Index for hours in the analysis, typically 8,760 hours for 1 year
L_h	System load in hour h (MW)
Bp_{Max}	Nameplate capacity of storage (MW)
Bl_{Max}	Maximum level of storage (MWh)
η	Roundtrip efficiency of storage (%)
H	Number of peak hours

2. Variables

Bo_h	Discharge power from storage to the grid (MW)
Bi_h	Charging power from the grid to storage (MW)
Bl_h	Storage level (MWh)
NL_h	System net load in hour h (MW)
NL^*_{H+1}	Net load in hour $H+1$ (a level chosen by the model)
π_h	Continuous auxiliary variable equal to the maximum of [NL_h-NL^*_{H+1}] and 0
ϵ	*De minimus* auxiliary variable to ensure charging in off-peak hours[2]

3. Objective Function

$$\min\left\{NL^*_{H+1} + {}^{1}\!/_{H} * \sum_{h=1}^{8760} \pi_h + \epsilon\right\}$$

4. Operational Constraints

Load and Net Load	$NL_h = L_h + Bi_h - Bo_h$
Identify Peak Hours	$\pi_h \geq NL_h - NL^*_{H+1}$
Ignore Net Load in Non-peak Hours	$\pi_h \geq 0$
Storage Energy Balance	$Bl_h = Bl_{h-1} + \eta \cdot Bi_h - Bo_h$
Maximum Storage Level	$Bl_h \leq Bl_{Max}$

[2] To account for the storage system's operation beyond peak hours, an additional term, ϵ, is added to the objective function, ensuring that storage is charged during off-peak hours. This term has a very small weight, such that it does not interfere with the CC calculation.

Maximum Storage Production $0 \leq Bo_h \leq Bp_{Max}$

Maximum Storage Charge $0 \leq Bi_h \leq Bp_{Max}$

Prefer Charging in Off-peak Hours $\epsilon \geq 10^{-8} * \sum_h L_h(Bi_h - Bo_h)$

2.3 Validation Against Probabilistic Benchmark

We compare the CC calculated with the LDC method versus the CC calculated as the ELCC using the probabilistic approach outlined by Keane et al. [30].[3] The probabilistic benchmark accounts for the probability that random forced outages at power plants will lead to insufficient generation to meet demand, as quantified by the loss of load probability (LOLP). Overall reliability is then measured by the loss of load expectation (LOLE), which accumulates the LOLP over all hours. The ELCC represents the amount that the demand can be increased after a resource is added to the generation mix while maintaining the same level of overall reliability. To validate the LDC method for storage, we calculate storage's ELCC using the storage dispatch profile that results from the linear storage dispatch model.

2.4 Importance of Forecasting

In our storage dispatch model, we assume that storage can be dispatched with perfect foresight. Though this is not feasible, it provides an upper bound to the achievable CC as defined by the LDC method. We find a lower bound by implementing a feasible, though naïve, dispatch strategy: dispatch the storage today based on the optimal dispatch schedule for yesterday's load. Clearly this naïve dispatch strategy could be improved using state-of-the-art forecasting. In our analysis, however, it simply provides a lower bound that can be calculated without making assumptions about forecasting capabilities.

3. Case Study Data and Assumptions

An advantage of the LDC method is that it requires relatively little data, only the load and the resource generation profile. Our case study quantifies the CC of solar and storage using load data from three municipal utilities: JEA, City of Tallahassee, and the Florida Municipal Power Pool (FMPP[4]). Hourly load data for the three utilities were obtained from ABB Velocity Suite (based on Federal Energy Regulatory Commission Form 714) for 2006–2016. Solar generation data for the same period were generated using the default assumptions in NREL's PVWatts model, with

[3] The level of reliability based on the generation and demand can change from year to year. Similar to the approach used by Madaeni et al [10], we scale the load levels so that the LOLPs of the base system in each year sum to 2.4 in order to have a consistent starting point for determining the reliability contribution of solar and storage.

[4] FMPP member utilities include the Orlando Utilities Commission, Lakeland Electric, and the Florida Municipal Power Agency. FMPP operates the combined resources of the utilities as if they were one utility.

historical weather data sourced from the National Solar Radiation Database for particular hypothetical PV sites located near each utility (Figure 2).

For the probabilistic benchmark, we also require the nameplate capacity and forced outage rate for generators associated with each utility, which we obtained from ABB Velocity Suite augmented with 10-year site plans filed with the Florida Public Service Commission. For the City of Tallahassee, a small utility with two relatively large generators and a limited number of small generators, we also include 200 MW of firm capacity based on transmission capacity between the City of Tallahassee and resources in Georgia. This transmission capacity is not tied to any one generator, but provides the City of Tallahassee with access to a wide variety of resources at times when its own units experience forced outages.

Throughout the analysis, we assume storage has a roundtrip efficiency of 85%.

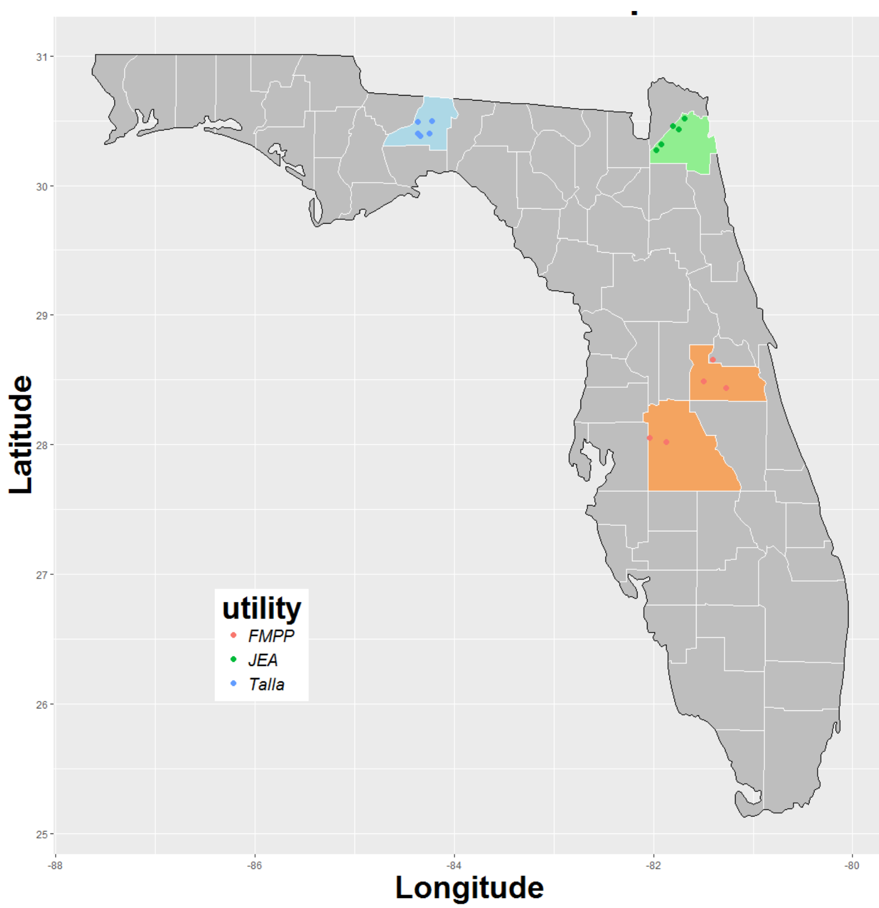

Figure 2. Location of hypothetical PV sites in Florida.

4. Results

We use the LDC method to find the CC of solar, storage, and different configurations of solar + storage. We then validate the results from the LDC method against a probabilistic benchmark and find a lower bound to the CC of storage associated with forecast errors. The following are our key results.

4.1 Capacity Credit of Solar Varies by Utility and Weather Year

Using the LDC method, we find that solar's CC varies from one utility to another, and it varies by weather year (Figure 3a). The CC of solar is highest (about 30%–50% of nameplate capacity) when using the hourly load shapes from FMPP along with the solar generation patterns from hypothetical sites near FMPP. The CC is somewhat lower (about 20%–40%) when using the load shapes and solar generation data for JEA and the City of Tallahassee. The primary reason for the higher solar CC in FMPP is that almost all of the peak 100 load hours occur on summer afternoons, whereas JEA and the City of Tallahassee also have peak load hours during winter mornings or nights when solar generation is minimal or zero.

Though there is a large range in solar CC across years, only a few particular years drive that range. The CCs calculated using the full 11 years of data, represented by the colored dots in Figure 3a, are close to the medians of the CCs calculated from each year individually. In addition, the CC varies very little with the choice of hypothetical sites within the relatively small footprint of the utilities.[5] As such, for the remainder of this analysis, we present results from only one PV site within each utility. We also focus the rest of our analysis on a single weather year, 2012, because this is the weather year used in the current version of RPM for all demand, wind, and solar shapes. The 2012 weather year yields CC estimates that are close to the medians across all 11 years (Figure 3b).

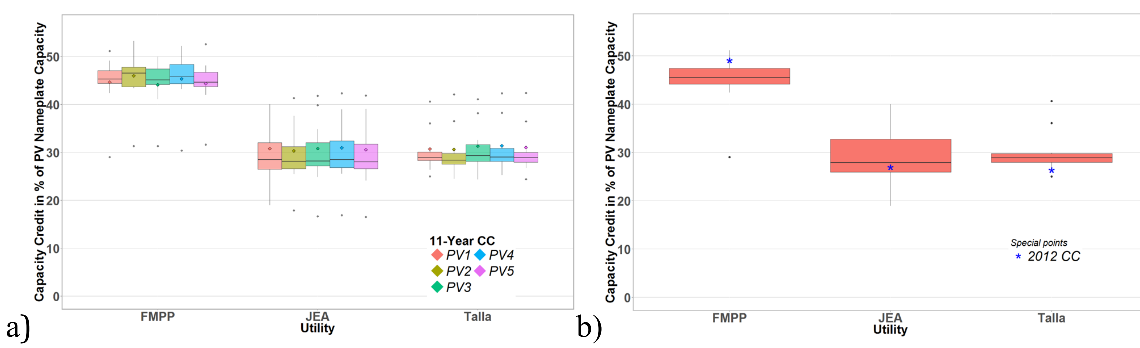

Figure 3. Variability in solar CC across each of the 11 weather years and 5 PV sites compared to the solar CC from the full 11 years of data (a) and comparison of the CC from the 2012 weather year to all other years for the one representative PV site (b).

The CCs of solar calculated with the LDC method are within the range of solar CCs, at low penetrations, reported in other studies or assumed in utility planning studies,

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[5] We also find that geographic diversity within the region around the utilities does not significantly impact the solar CC. We conducted a simple experiment where the CCs of hypothetical sites were estimated individually then compared to the CC of a similar amount of aggregate PV distributed across multiple sites. The aggregate CC was not noticeably greater than the average of the individual site CCs. Geographic diversity can, however, help mitigate sub-hourly variability even for sites within a utility service territory [31], [32].

though at the lower end [2], [12]. The LDC method yields a solar CC that is somewhat lower than the 54% CC assigned to solar by a major investor-owned utility, Florida Power & Light (FPL), in its cost-effectiveness evaluation. FPL estimates the CC based on the expected solar generation during the typical peak demand periods of 4-5pm in August. FPL also estimates CC for the winter period, based on generation between 7-8am in January, finding little contribution to reliability in this period because the winter peak occurs when solar generation is low. Because the peak is higher in summer than in winter, FPL finds that solar can defer the need to build new capacity commensurate with solar's summer CC [33].[6]

4.2 Capacity Credit of Solar Declines with Increasing Solar Deployment

Consistent with findings in the literature, solar's CC based on the LDC method declines with increasing solar deployment (Figure 4), primarily because more solar shifts the peak net load hours away from summer daytime hours and into early evening hours in the summer or early morning hours in the winter. Adding solar does little to reduce the peak net load in these hours, thereby lowering solar's CC. This trend is consistent across the three utilities. By the time solar deployment has increased to generate enough energy to meet 15% of annual sales, the average CCs are less than half of the CCs at very low deployment levels. The reduction in solar CC with higher deployment is helping to drive interest in solutions that ensure resources are adequate to meet demand, including adding storage.

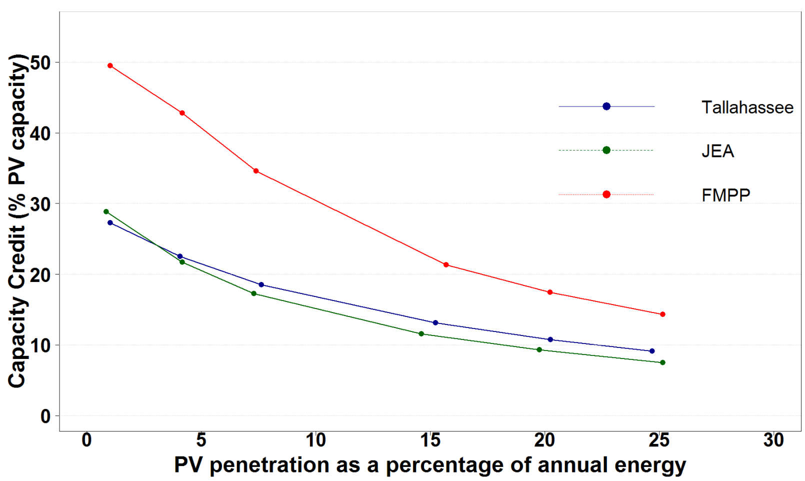

Figure 4. Declining average CC of solar with increasing solar deployment.

[6] The FPL example also highlights that utilities often calculate a summer and winter capacity contribution of resources. The RPM model, on the other hand, only uses a single value for the CC which is based on the highest peak hours across the entire year. Here we similarly present only the CC calculated using all hours of the year rather than partitioning the year by season.

4.3 Capacity Credit of Storage Depends on the Storage Duration and Declines with Increasing Storage Deployment

In contrast to solar, which has weather-dependent generation, storage is viewed as more reliable owing to its dispatchable nature. We find, however, that the fraction of storage's nameplate power rating that contributes to resource adequacy (i.e., storage's CC) is highly dependent on the duration of storage, which is based on the ratio of the energy capacity to the power rating. With too few hours of energy, storage cannot continuously reduce the peak net load hours on days with high, broad peaks. On these days, storage is more likely to be depleted when reducing peak load, leaving it unavailable for discharge during other peak hours. The impact of storage duration on storage's ability to reduce winter and summer peak load hours is illustrated in Figure 5. In this illustration, 1 hour of storage is insufficient to reduce winter or summer peaks, 4 hours is more effective in reducing the narrow winter peak and less effective for the broader summer peak, and 6 hours is effective in both winter and summer. This is just an illustration—the duration of summer and winter peaks varies from year-to-year and between utilities.

Also apparent in Figure 5 is that, for storage to continue reducing peak loads, broader and broader peaks must be clipped as more and more storage is deployed. Conversely, for the same hours of storage, the average storage CC is reduced as more and more storage is deployed. Figure 6 illustrates both the relationship between storage CC and hours of storage as well as the declining storage CC with increasing storage deployment, as calculated with the LDC method. Here the nameplate capacity is 0.3% of the peak load (low storage penetration requiring about 2–10 MW of storage depending on the utility) or 20% of the peak load (high storage penetration requiring about 120–600 MW of storage).

Across the three utilities, storage's CC, even though it is fully controllable by the system operator, depends strongly on the storage duration. Achieving a 90% CC requires at least 4–5 hours of storage at low storage penetration, when storage capacity is small relative to the system peak. As storage deployment increases to 20% of the peak demand, 9 hours—and sometimes more than 10 hours—of storage are needed to achieve a 90% CC. These findings, based on the LDC method for calculating CC, are in line with previous estimates based on more detailed probabilistic methods (e.g., [19]).

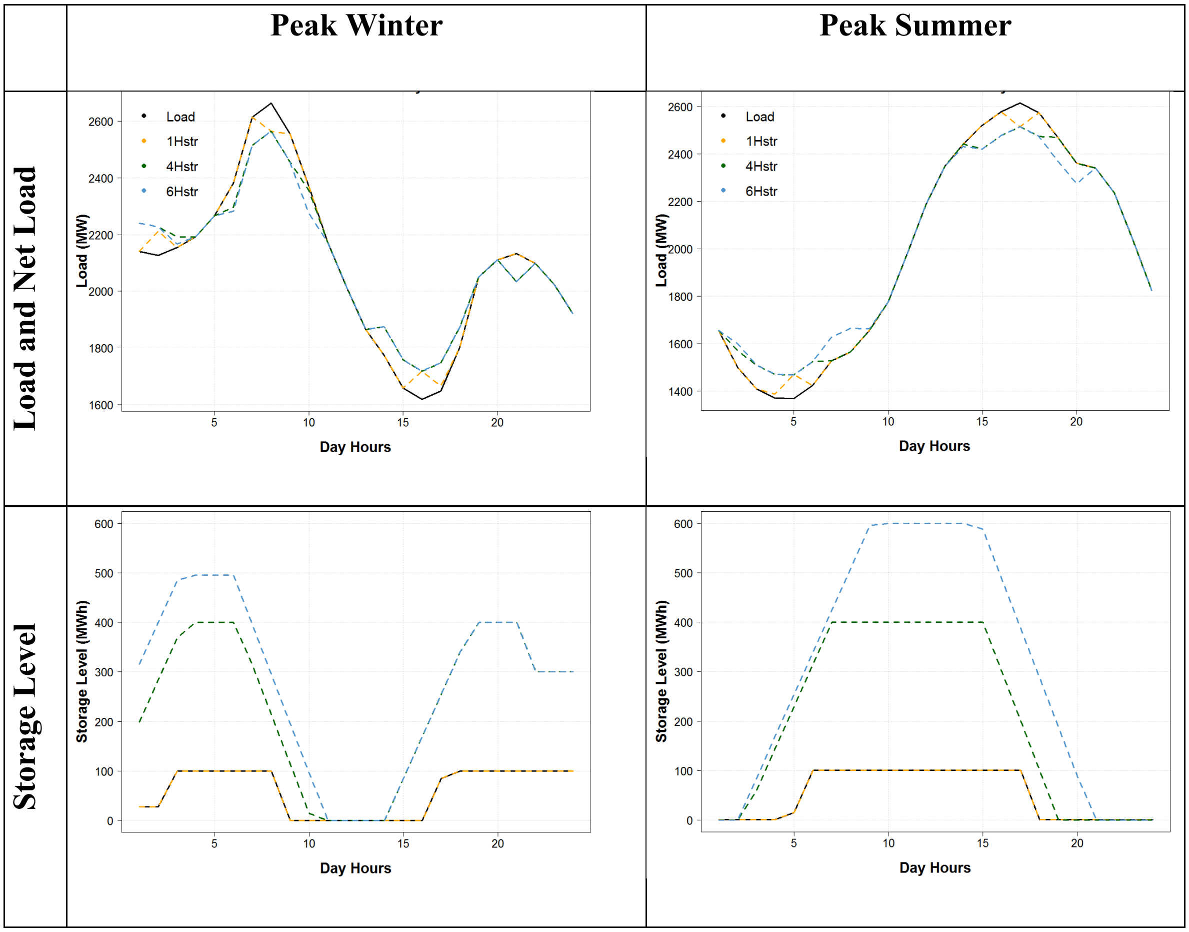

Figure 5. Load and net load (load less storage generation) for a peak winter and summer day with varying storage reservoir sizes.

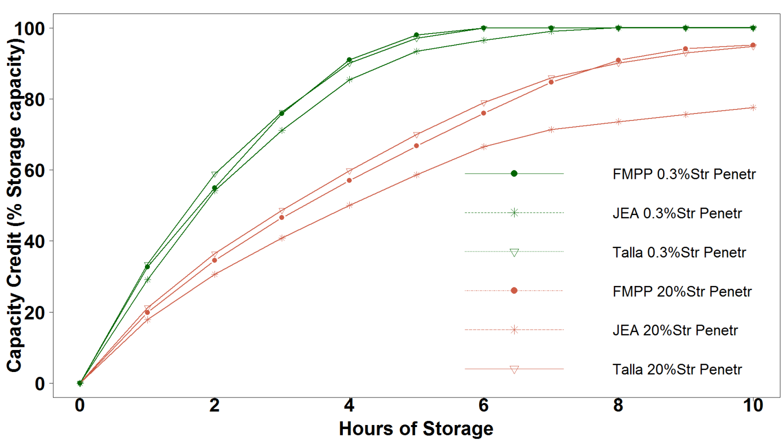

Figure 6. Dependence of storage CC on storage duration, declining CC with increasing storage deployment.

4.4 Capacity Credit of Storage Can Vary with Weather Year

Because storage's CC depends on load shape, it can vary from year to year. Based on the findings in Section 4.3, storage with a given duration is more likely to have a higher CC in years with narrower peaks, while achieving a high CC in years with broader peaks requires longer-duration storage. As Figure 7 shows, for FMPP, the variation in storage CC with weather year is largest for medium-duration storage (3–5 hours). For short-duration storage (1 hour), the CC is small across all weather years. For long-duration storage (10 hours), the CC is close to 100% in almost all weather years. Overall, the variation in storage CC with weather years (Figure 7) is somewhat smaller than the variation in solar CC for FMPP (Figure 3). Qualitatively similar patterns were observed for the variation in storage CC using the other utility load shapes.

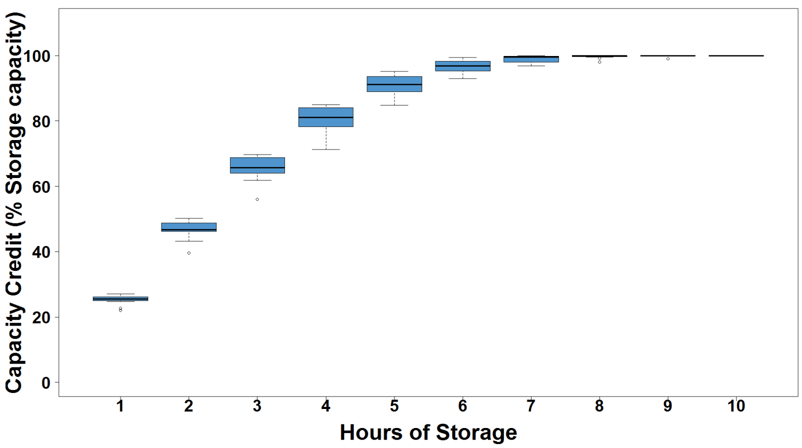

Figure 7. Variation in storage CC by weather year and storage duration, for 100 MW of storage in FMPP.

4.5 Capacity Credit of Storage Depends on System-Level Solar Deployment

Seeing the dependence of storage CC on the width of peaks, we expect the storage CC to change as net load peaks narrow with increasing solar deployment. To test this, we compare the decline in storage CC with increasing deployment of 4-hour storage under a case with no system-wide solar and a case with as much as 15% of the annual energy being met by solar (Figure 8).

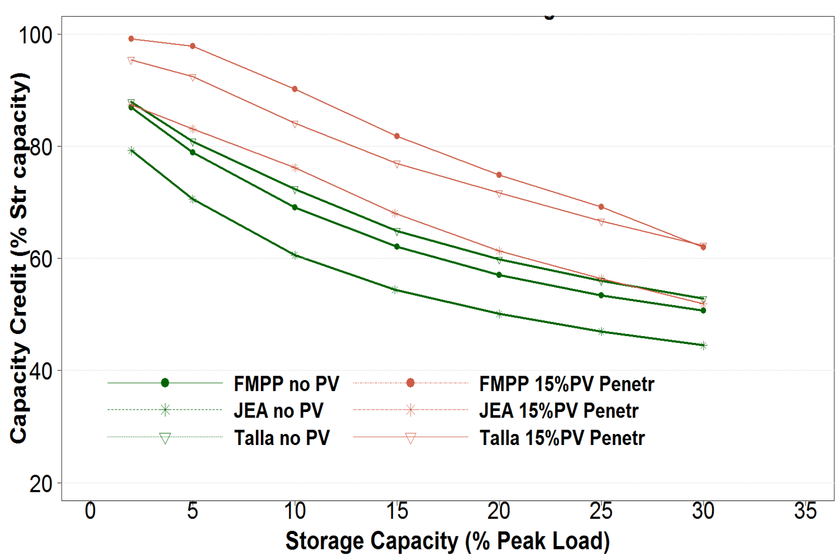

Figure 8. Impact of system-wide solar deployment on storage CC, 4-hour duration storage.

The CC of 4-hour storage is greater with system-wide deployment of solar than without solar, though the storage CC still declines with increasing storage deployment. The increase in 4-hour storage CC with system-wide solar deployment is greatest for FMPP, the utility with a load shape that peaks only in the summer and therefore likely sees the greatest change in peak net load shape with solar. The effect is smaller for the two utilities (JEA and the City of Tallahassee) that tend to have some peak load hours in winter mornings or late winter nights.

For storage with a duration shorter or longer than 4 hours, the storage CC follows a similar declining trend with increased deployment of storage, though with some differences. For shorter duration storage, the storage CC begins at a lower level, hence the decline with increasing storage deployment appears flatter. For longer duration storage, the storage CC begins at a level closer to 100% CC and maintains that level before beginning to decline as storage deployment increase.

Here we present only the incremental CC of storage with and without large shares on solar on the system. Storage deployment can also increase solar's CC at high solar penetrations, though we do not show that here. The interaction between the CCs of storage and solar demonstrates a synergy that may be important to capture in capacity-expansion models. In the next section, we analyze the CC of solar + storage facilities, though only at low penetration. We leave further investigation of synergies at very high penetrations of solar and storage to future studies.

4.6 Solar + Storage Configuration Affects Capacity Credit

Increasingly, storage is considered as a resource that can be combined with solar to create a dispatchable resource similar to concentrating solar power with thermal storage [34]. Though there are many factors to consider when sizing storage and solar and deciding on the configuration, we focus solely on the implications for the CC of solar + storage.

The factors that can be adjusted when designing a solar + storage system include the number of hours of storage, the storage power capacity relative to the PV module capacity, the ratio of the inverter capacity to the PV module capacity, whether the solar and storage are independent (alternating current [AC] coupled) or share an inverter (direct current [DC] coupled), and whether the storage can charge from the grid or solar (loosely coupled) or whether it can only charge from solar (tightly coupled).[7] One reason to model a restriction under which storage can only charge with solar power relates to tax credit policy. Currently, storage can qualify for the U.S. federal Investment Tax Credit (ITC) that is available for solar plants if the storage charges from solar at least 75% of the time. We consider the implications on solar + storage CC by comparing results for the extreme case in which storage is only charged from solar or it can be charged from either the grid or solar (Table 1). In all coupled cases, we assume that the ratio of the inverter capacity to the PV

[7] We follow the naming convention for this configuration as described by Denholm et al. [35]

module capacity is kept constant, rather than changing the inverter size as storage is added.

Table 1. Definition of Analyzed Solar + Storage Configurations

Configuration	Description	Share Equipment?	Source of Electricity for Storage
Independent	PV and storage do not share equipment, and storage is charged from the grid.	No	Grid
Loosely Coupled	PV and storage both connect on the DC side of shared inverters, but storage can charge from storage or the grid.	Shared inverter	Grid or PV
Tightly Coupled	PV and storage connect on the DC side of shared inverters, and storage can only charge from PV.	Shared inverter	Only PV

In the independent case, the CC of a solar + storage system is equivalent to the sum of the CC of solar alone and the CC of storage alone. When coupling solar and storage together with a shared inverter, the CC can be less than the sum of the individual CCs if the shared inverter limits the joint production of solar and storage or, in the case of the tightly coupled system, the solar is insufficient to fully recharge the storage before the next system peak.

Using JEA load and solar data for 2012 along with the assumption that storage and PV both have a nameplate capacity of 100 MW, we find examples in which a coupled solar + storage system can have a CC less than the CC of an independent system or even less than the CC of storage alone (Figure 9a). In this particular case, the CC of solar + storage is not impacted by configuration for short-duration storage (1 hour). Increasing the duration, however, produces a gap between the CCs of independent and coupled systems. The CC of the loosely coupled solar + storage system is limited by the capacity of the shared inverter. Requiring storage to only charge from solar (tightly coupled) further restricts the CC; at 6 hours of storage and above, the CC of the tightly coupled solar + storage system is less than the CC of storage alone (which can charge from the grid during off-peak hours). Similar behavior is observed with the FMPP load and solar data, but with less difference between the CC of the tightly and loosely coupled configurations and the CC of solar + storage is never less than the CC of storage alone (Figure 9b). The reason the solar + storage CC is less impacted by restricting charging to solar in FMPP than in JEA may be that FMPP peak hours all occur in the summer, when solar production is greater and more consistent, while some of the JEA peak hours occur in the winter, when solar production is lower. In addition, the duration of peaks is wider for JEA than for

FMPP; wider peaks require more energy, which is limited by solar generation in the tightly coupled case.

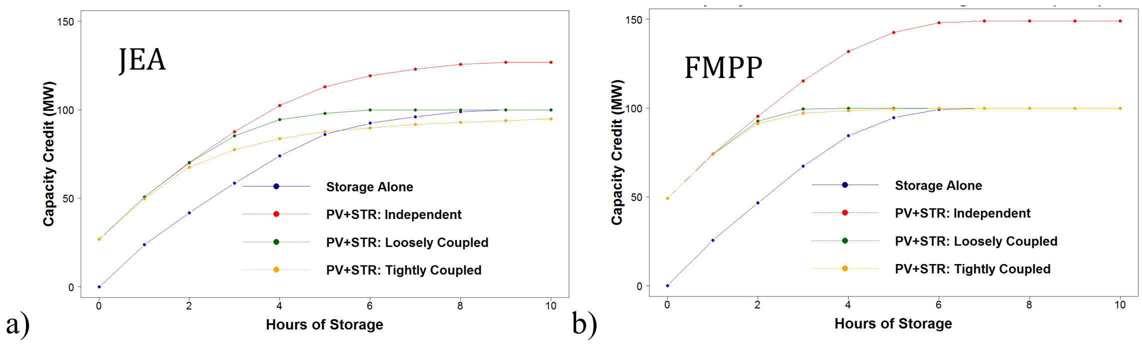

Figure 9. Variation in solar + storage CC with different configurations with 100 MW storage and 100 MW of solar using (a) JEA and (b) FMPP load and solar profiles from 2012.

We find that if the storage size is reduced to only 20% of the solar nameplate capacity, the CC of solar + storage is nearly equivalent across the independent, loosely coupled and tightly coupled configurations. With storage sized well below the inverter capacity, and the CC of solar less than 50% of its nameplate capacity, there are few opportunities for storage and solar to compete for limited inverter capacity. Likewise, in the tightly coupled case, a much smaller amount of solar is required to charge the smaller storage system, making storage easier to charge only with solar energy.

Even if storage and solar are equally sized, it may be possible to achieve the same (or similar) CC with a coupled system as with an independent system if the inverter capacity is increased in the coupled system. This increases the cost of the coupled system, but it may be worth the cost if reliability is a high priority for the utility. The requirement to only charge storage from solar in the tightly coupled case may continue to be a limiting factor.

4.7 Capacity Credit Calculated with LDC Method is Consistent with Probabilistic Benchmark Except for Very Small Utilities

As mentioned in the Introduction, the LDC method is convenient for easily and transparently evaluating the CC of solar and storage under many different possible weather years, combinations of hypothetical sites and utilities, and system configurations. To be useful in decision making, however, it should also yield reliability estimates similar to those derived from a more detailed evaluation with probabilistic reliability methods. Here we validate the approximation by comparing the CC estimated with the LDC method to the ELCC calculated with a probabilistic method (Figure 10). We develop storage dispatch profiles such that they maximize storage CC under the LDC method, and then we apply those profiles in the ELCC calculation. In both methods, we use the same solar, load, and storage dispatch data. The only additional information used in the probabilistic method is the capacity and forced outage rate of the conventional generation operated by the utilities.

For the two larger utilities with peak demand over 3 GW (JEA and FMPP), the CC with LDC method is directionally consistent and quantitatively similar to the ELCC calculated with the probabilistic methods for solar and storage. For these two utilities, the main difference is that the LDC method tends to overestimate the CC of solar and storage, particularly for longer durations. Even for the small utility with a peak demand of less than 1 GW (City of Tallahassee), the solar CC with the LDC method is somewhat similar to, though slightly higher than, the ELCC.

On the other hand, for the small utility (City of Tallahassee), the CC of storage estimated with the LDC method is much greater than the ELCC. This starkly different result stems from the small number of conventional generating stations operated by Tallahassee, with some relatively large compared to the load, which leads to a widely distributed risk of outages (or a widely distributed LOLP). Whereas the risk is concentrated in less than about 0.5% of the hours for JEA and FMPP, Tallahassee's risk is distributed over about 17% of the year.[8] As a result, short-duration storage makes a much smaller contribution to increasing the overall system reliability for the City of Tallahassee compared to the contribution of storage in JEA and FMPP.

Though the deviation between the CC estimated with the LDC method and the ELCC for the City of Tallahassee is important to understand, we consider this to be a rare failure of the approximation rather than a common occurrence. Few utilities are as small as the City of Tallahassee, and even among small utilities it is rare to find individual generators that constitute such a large fraction of the total capacity. More generally, since we largely treat each utility as an island, we do not model several factors that could be important in determining the true risk profile for utilities including the potential to access generation over other transmission lines and to leverage shared reserves for short-term events. Probabilistic methods that can account for transmission capacity to neighboring utilities exist [36], [37], though we do not consider those approaches in this simple validation.

[8] We measure the concentration of the risk of outages as the percentage of hours in which the LOLP is greater than 5% of the maximum LOLP. A smaller percentage of hours in which the LOLP is greater than 5% of the maximum indicates that the risk of outage is more concentrated in peak hours.

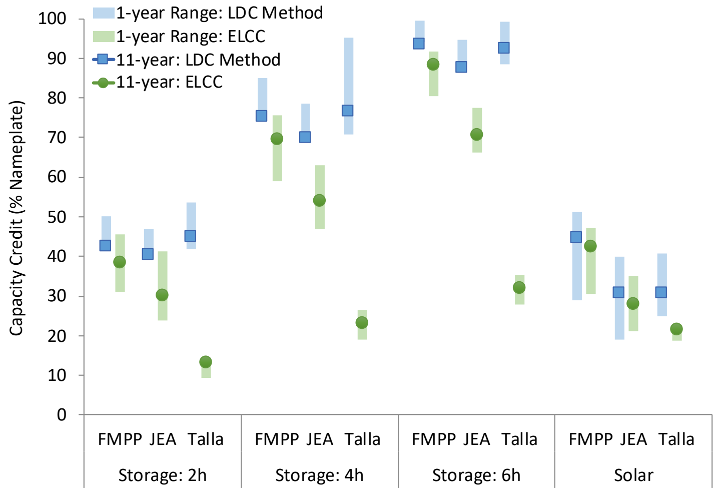

Figure 10. Comparison of the CC estimated with the LDC method to the ELCC calculated with a probabilistic method.

4.8 Forecasting Matters for Storage Capacity Credit, Particularly with Small Storage Reservoirs

Throughout the preceding analysis, we estimate an upper bound to storage's CC with the LDC method assuming that demand could be perfectly forecast. In reality, storage dispatch will depend on many factors, including how well peak periods are forecasted. A lower bound to the storage CC can be established by assuming that the schedule based on the previous day's observations is implemented in the current operating day. This naïve "day-ahead persistence" dispatch approach is practicable, though it should be easy to improve by considering information like weather forecasts in the dispatch development.

We find that the impact of forecasts on storage CC is more important for shorter-duration storage than for longer duration-storage. We illustrate this in Figure 11 by showing the fraction of the perfect foresight CC achieved with storage dispatched with day-ahead persistence. With 1-hour storage, for example, the optimal storage schedule with perfect foresight often results in storage being fully discharged in the peak hour. If, however, the peak hour in the previous day shifts by as little as an hour during the operating day, the contribution of storage to meeting peak hours could be greatly diminished. With 4 hours of storage, however, the dispatch often discharges the storage over the highest 4 hours of a day. Even if the peak shifts by 1 hour from one day to the next, the storage dispatch profile is much more likely to reduce demand in that hour. Forecasting is particularly important for a small utility (the City of Tallahassee) with variable peak hours.

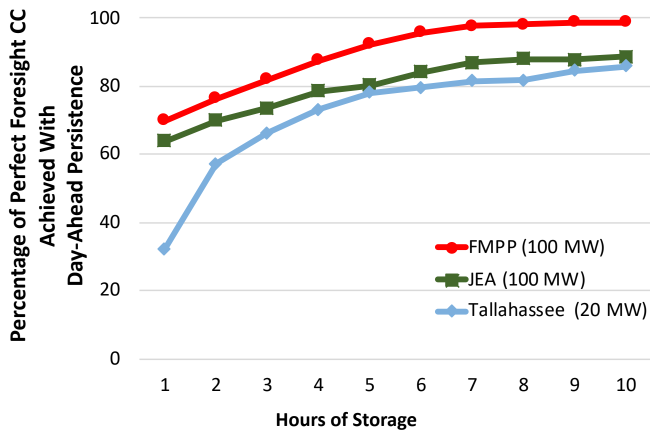

Figure 11. Importance of forecasting to the CC of storage.

5. Conclusions

Many factors impact the CC of solar and storage, including weather, utility demand profiles, solar and storage deployment levels, and the configuration of solar and storage systems. Exploratory analysis of the relative importance of different factors can be useful before evaluating specific cases via more detailed and resource-intensive modeling. We have developed and demonstrated a fast and relatively simple algorithm for identifying the dispatch that maximizes the CC of storage and solar, suitable for such exploratory analysis.

Applying this approach to a case study in Florida, we find that storage's CC—even though it is fully controllable by the system operator—strongly depends on the storage duration. Achieving a 90% CC requires at least 4–5 hours of storage when storage capacity is small relative to the system peak. As with solar, the CC of storage can vary with weather year, though it is somewhat less sensitive to year-to-year variations, and the variability tends to be largest with moderate storage durations (e.g., 3–5 hours). As storage deployment increases to 20% of the peak demand, 9 hours—and sometimes more than 10 hours—of storage are needed to achieve a 90% CC. Or from another perspective, the CC of storage with the same duration will decline with increasing storage deployment.

Increased solar deployment at the system level can increase the CC of 4 hours of storage. Directly pairing solar and storage can also impact the CC. Storage with a power rating similar to the solar inverter rating loses CC when coupled with solar if its duration is more than 1–2 hours, because storage competes with solar for use of the inverter. Restricting storage to only charge with solar can reduce the CC of a solar + storage system, sometimes to the point that it becomes smaller than the CC of storage alone. On the other hand, there is no reduction in CC when the storage is small relative to the solar inverter.

Several directions for future work emerge from this analysis. First, the optimal configuration of solar and storage depends on much more than maximizing the resource adequacy contribution [35]. Storage might reduce solar's levelized cost of energy, especially when the PV panels are oversized relative to the inverter, by charging coupled storage using energy that would otherwise be clipped. Storage can also provide additional value streams beyond the capacity value, including energy value and ancillary services. It can also smooth the solar production profile due to passing clouds. Future analysis could investigate how the different uses of storage alter the optimal solar + storage configuration and whether any of these other factors affect the CC. Second, we see evidence of synergy, with high solar penetrations increasing storage's CC and high storage penetrations increasing solar's CC. This synergy may be important to capture in capacity-expansion models. Finally, our CC approximations appear to mimic results from more detailed probabilistic methods, except for a very small utility with relatively large generators and widely distributed high-risk hours. Additional analysis could more broadly investigate the circumstances that cause the approximations to deviate from the probabilistic results.

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Appendix

Storage CC estimation strongly depends on the storage dispatch, that is, the decisions about when and how much batteries or other storage systems are charged and discharged. There are many ways in which storage can be operated depending on the target the operator has in mind. Typically, the dispatch is decided by means of a linear model that minimizes system operation cost [20] or maximizes benefits during a certain time scope [38]. However, to our knowledge, there is no developed method to optimize the operation of batteries during a specific time scope in order to maximize the CC. We develop a model based on linear programming that can maximize the CC provided by a storage facility.

Because the proposed model is only focused on the operation of the storage to maximize the CC, additional generators and their costs and operating constraints are not modeled. The system as a whole is defined through an hourly load curve and a certain storage capacity. The time scope is a year, with hourly detail; that is, the decision variables are the charge and discharge of the batteries for each hour of the year. Chronology is considered in the model using historic load curves. This chronology provides realistic storage operation decisions.

The model uses a novel application of the conditional value at risk (CVaR) optimization algorithm, first developed for finance applications, to solve the CC maximization for storage. Hence, we first review the basics of the CVaR optimization formulation, before introducing its adaptation to CC maximization.

CVaR Optimization Formulation

In mathematical finance theory, one of the most widely used coherent measures of risk is the so-called CVaR index [28]. The VaR (value at risk) calculates the losses of an investment portfolio with a specified probability. For example, the losses of an investment will have a 5% probability of being higher than the VaR at 95%. The CVaR at 95% represents the average losses in those 5%-probability worst cases. Thus, it is directly proportional to the area of the density function for those 5% worst cases.

The CVaR optimization formulation tries to minimize the risk associated with buying a portfolio of assets by minimizing the obtained CVaR at a certain percentile (%), according to different returns associated with several scenarios.

Given a portfolio of n assets, let X_i be the per-unit amount of each one:

$$\sum_{i=1}^{n} X_i = 1$$

Let $s = 1,\ldots,S$ be the different scenarios considered for the evolution of the price of the different assets. For each considered scenario s, the losses per stock can be calculated as the product of the per-unit amount times the loss r_{is} for each asset in each scenario. Hence, the total losses for each scenario can be calculated as:

$$L_s = \sum_{i=1}^{S} X_i . r_{is}$$

Having the density function for the total losses, and given a percentile, the VaR is defined as the value of the density function at that specific percentile (α). Typically, a 95% percentile is used ($VaR_{95\%}$). As mentioned, the CVaR is defined as the mean of losses in the 5% (or whatever VaR) tail of the distribution (Figure 12).

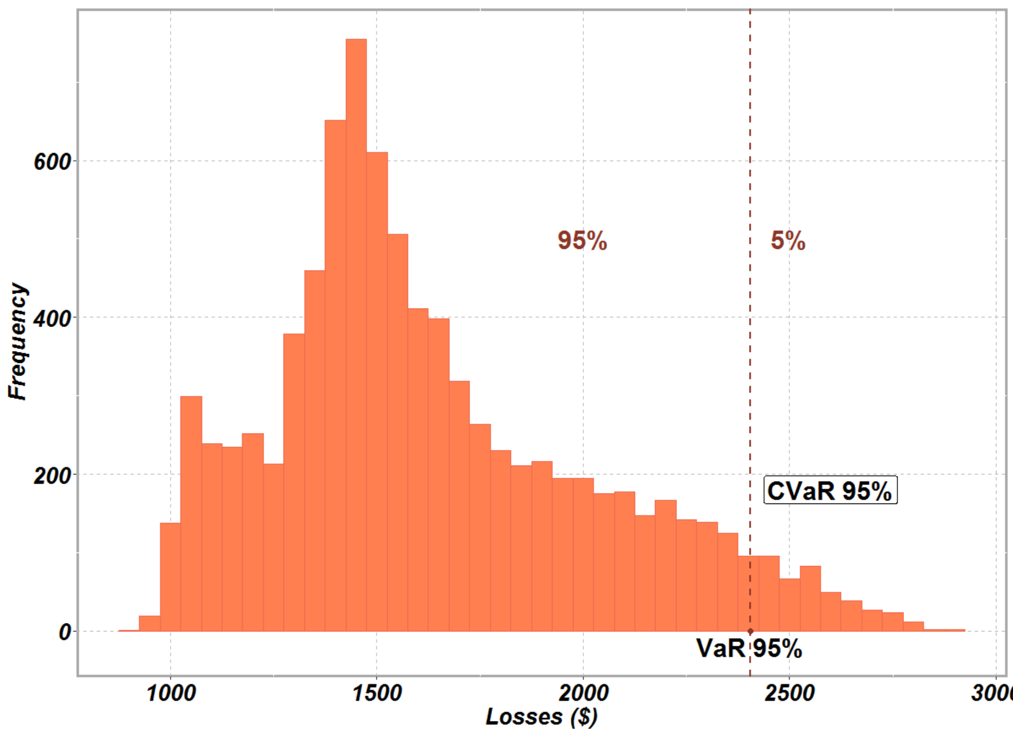

Figure 12. Histogram of a losses density function highlighting VaR and CVaR for a 95% percentile.

The CVaR minimization for a percentile α can be expressed using the following expression:

$$CVaR_\alpha = \ min_{VaR,X_i,L_s} \left\{ VaR_\alpha + \frac{1}{1-\alpha} \ \mathbb{E}[max(L_s - VaR_\alpha, 0)] \right\}$$

Rockafellar and Uryasev [28] proved that this CVaR minimization can be solved by using the following linear optimization problem:

$$min_{VaR,X_i,u_s} \left\{ VaR_\alpha - \frac{1}{(1-\alpha)\cdot S} \cdot \sum_{s=1}^{S} u_s \right\}$$

s.t.

$$u_s \geq \sum_{i=1}^{n} X_i . r_{is} - VaR_\alpha \; s = 1, \dots, S$$

$$\sum_{i=1}^{n} X_i = 1$$

$$u_s \geq 0 \; ; X_i \geq 0$$

This methodology can be applied in other contexts where areas below some curves must be minimized or maximized. Particularly, the CVaR model can be adapted to maximize the CC in a set of hours, as explained in the next section, because the final objective is to minimize the area below the net load curve during peak hours.

Application of CVaR Optimization to Capacity Credit Maximization

The application of the CVaR optimization to the maximization of the CC for storage facilities can be understood through an analogy between the different problems to be solved.

On the one hand, as abovementioned, CVaR minimization can be expressed through the following non-linear expression:

$$CVaR_\alpha = \; min_{VaR, X_i, LS} \left\{ VaR_\alpha + \frac{1}{1-\alpha} \; \mathbb{E}[max(L_s - VaR_\alpha, 0)] \right\}$$

On the other hand, trying to maximize the CC is equivalent to minimizing the net load *NL* for the *H* peak hours. Minimizing the net load can be carried out through a minimization of the area below the net load-duration curve for the first *H* hours. This area can be minimized as:

$$Area_H = \; min_{D_{H+1}, X, NL_h} \left\{ NL^*{}_{H+1} + \frac{1}{H/8760} \; \mathbb{E}[max(NL_h - NL^*{}_{H+1}, 0)] \right\}$$

Where, as shown in Figure 13 and Figure 14, NL^*_{H+1} represents the net load level at hour *H+1*, NL_h the net load for hour *h*, and *X* the batteries operating decisions (subject to all the operational and technical constraints of the storage system, such as chronology, maximum level of storage, and maximum output).

Hence, we can make an analogy between both problems and use an equivalent linear problem to solve the CC maximization. In this analogy, the losses for each stock are analogous to the net load of the system after the storage dispatch for every hour has been determined.

Scenarios in CVaR minimization will be substituted by hours in CC maximization. Regarding the decision variables, unlike what happens in the CVaR formulation in which the number of scenarios is limited, the number of possible storage-management options is infinite for CC maximization. That is why the net load variable uses only one sub-index in the new model formulation, instead of two as in the losses variables for the CVaR problem.

Following with the analogy, the confidence level α will correspond to the ratio of non-peak hours, that is *(8760-H)/8760* (Figure 13).

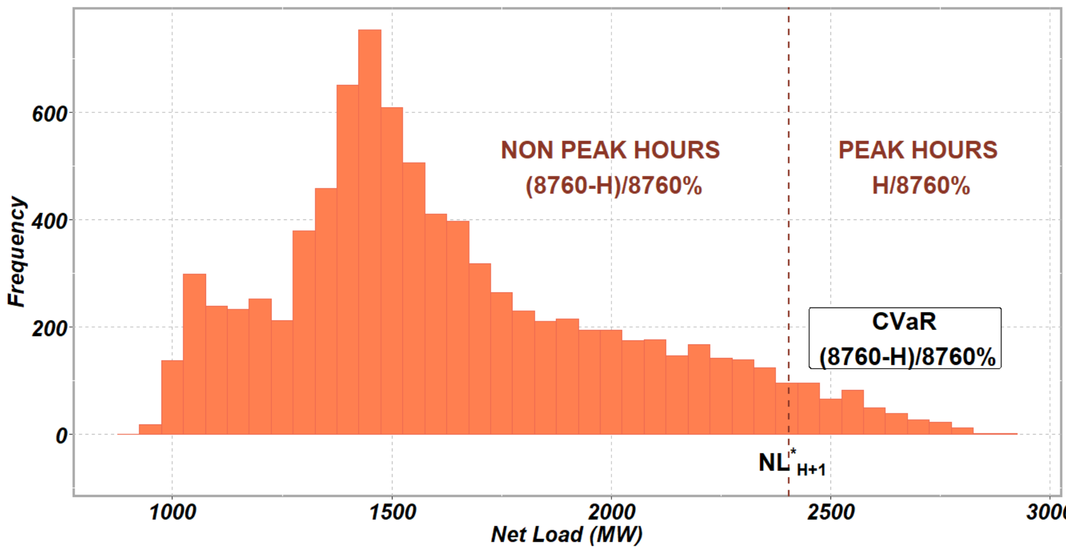

Figure 13. Histogram of a net load density function highlighting net load in the last peak hour and CC for H of peak hours.

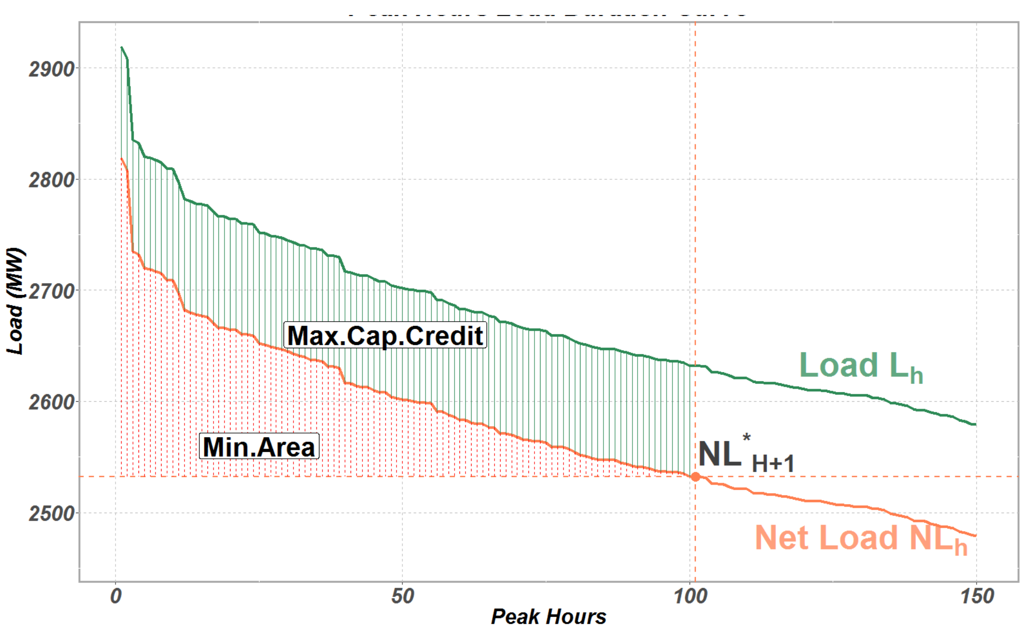

Figure 14. Maximizing the CC with the LDC method is equivalent to minimizing the area below the net load duration curve in the peak net load hours.

The parallelism between both formulations is summarized in Table 2.

Table 2. Analogy Between CVaR and CC Formulation.

CVaR formulation	**CC formulation**
O.F.: **Min CVaR**	O.F.: **Max CC** = **Min Average Net Load for H peak hours**
$\mathbf{VaR_\alpha}$	Net Load for hour H+1 in the net load duration curve $\boldsymbol{NL^*_{H+1}}$
Confidence level α	Ratio of non-peak hours ***(8760-H)/8760***
Scenarios s = 1,…,S	Hours h = 1,…,8760
Losses ($\mathbf{L_{ij}}$)	Net load ($\mathbf{NL_h}$)
Stock portfolio decisions	Battery operation decisions

Having this analogy in mind, the CC-maximization problem can be solved using an equivalent linear programming problem, as presented for the CVaR minimization. This model is presented above in Section 2.2.